Proceedings – 23rd Annual Conference – IEEE/EMBS Oct.25-28, 2001, Istanbul, TURKEY

COHERENCE ANALYSIS OF THE ONGOING EEG BY MEANS OF MICROSTATES OF SYNCHRONOUS OSCILLATIONS

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Abstract-**The sensitivity of instantaneous EEG coherence for the investigation of elementary thinking processes was shown by several authors. Similarly to EP analysis the statistical validation of the results is based on the multiple repetition of the same task. This approach is not possible for complex unreproducible thinking processes of long duration as e.g., solving mathematical problems. Classical coherence analysis of long periods of the EEG suffers from the loss of temporal information. The paper presents a temporal coherence analysis of the ongoing EEG preserving the temporal information of long cognitive processes.**

The main point of the method is the decomposition of the whole time interval in microstates of synchronous oscillations. The calculation of instantaneous coherence for multiple electrode pairs yields in a time-dependent high-dimensional coherence vector. A segmentation algorithm dissects the whole process into time intervals with stable coherence vectors- the so-called microstates of oscillations. A subsequent clustering procedure into a small number of classes results in a sequence of prototypical microstates, which may be modeled by a Markovian process. Special entropy parameters characterize the strength of concatenation of different microstates.

The method was applied in order to understand the special brain functioning of mathematically highly gifted subjects.

***Keywords* - Coherence, EEG, microstates, entropy, mathematical giftedness**

I. INTRODUCTION

EEG coherence analysis is widely used for the investigation of cognitive processes. Generally, complex cognitive processes of long duration are analyzed by coherence, estimated on the basis of the Fourier transformation, see e.g. [1]. Modern approaches allow the estimation of coherence continuously in time and the analysis of short-term cognitive processes, see e.g. [2], [3]. In the case of short-term cognitive processes the results were statistically validated by multiple repetitions of the task.

The EEG coherence analysis during thinking processes of solving mathematical problems require the temporal information of synchronization processes. A repetition of the same task is not possible for one subject. The solving process varies very strongly for different subjects.

There arises the problem of temporal coherence analysis of the ongoing EEG. One possible approach is the decomposition of the whole long time interval into microstates of timely stable synchronous oscillations. A special segmentation algorithm of the multi-dimensional time-dependent coherence vector was developed. A clustering procedure yields prototypes of microstates, which characterize different states of neural network synchronization. These prototypical microstates are characterized by their coherence values as a topographical information and their duration as a temporal information. The modeling of the sequence of microstates as a Markovian process allows the sequential analysis of a thinking process. Transition probabilities and the entropy reduction as measures of concatenation characterize the generation of order in the thinking process.

The EEG of two groups of subjects, mathematical gifted and normal pupils, was recorded during solving mathematical problems. A microstate analysis of synchronous oscillations was performed. In the case of complex problems a higher entropy reduction could be shown for mathematically gifted subjects. Moreover, microstates with long duration are significantly different for the two groups.

II. METHODOLOGY

Estimation of instantaneous coherence

An adaptive estimation method of the coherence function is used which allows high time and frequency resolution. The basic idea of the method is as follows: a pair of EEG channels is understood as a two-dimensional instationary signal process. This process is modeled as a two-dimensional autoregressive moving-average model with time-dependent parameters. The optimization criterion for adapting parameters is the minimization of the prediction error of the model in the least mean square sense. The correction of the model according to this criterion is performed at every sample point. Thus, the parameters of the model are functions of time and allow the parametric calculation of the momentary spectral density matrix of the ARMA model, which approximates the spectral density matrix of the underlying pair of EEG channels for the momentary time-point. Subsequently, the continuous estimation of the coherence is derived from the momentary spectral density matrix of the fitted ARMA model. The interested reader can find the detailed estimation procedure in [4]. This approach allows the time-dependent calculation of the full coherence spectrum and therefore the predefinition of a sensitive frequency band for the investigation of the information processing considered. For a chosen frequency band $\left[\lambda_{low}, \lambda_{upper}\right]$ coherence for any arbitrary electrode pair (i,j) may be calculated as a function of time:

$$\left(\rho^2\right)_{t_k}^{(i,j)}, \ k = 1, 2, \ldots \qquad (1)$$

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[1] Supported by German Federal Ministry of Research (DFG Scha 741/1-4).

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Coherence Analysis of the Ongoing EEG by Means of Microstates of Synchronous Oscillations	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) Institute of Medical Statistics Computer Science and Documentation Jena University Jena, Germany	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)

Distribution/Availability Statement
Approved for public release, distribution unlimited

Supplementary Notes
Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom.

Abstract

Subject Terms

Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU

Number of Pages
4

where t_k, k = 1, 2, ..., denote the digital sample points.

The instantaneous coherence analysis was performed for 30 adjacent electrode pairs in the longitudinal and transversal directions (so-called local coherences). For a topographic presentation of local synchronization processes the mapping procedure for local coherences was used [4]. With this aim, fictive coherence positions were placed in the middle of the 30 adjacent electrode pairs considered. The linear interpolation procedure led to the local coherence map (see lower panel of Fig. 1).

Segmentation of the time course of multi-dimensional band coherences

The estimation procedure of instantaneous coherence described above for a given frequency band yields a 30-dimensional time-dependent vector of coherences. This coherence vector may be calculated for each sample point of each single task. For a data reduction the time courses of

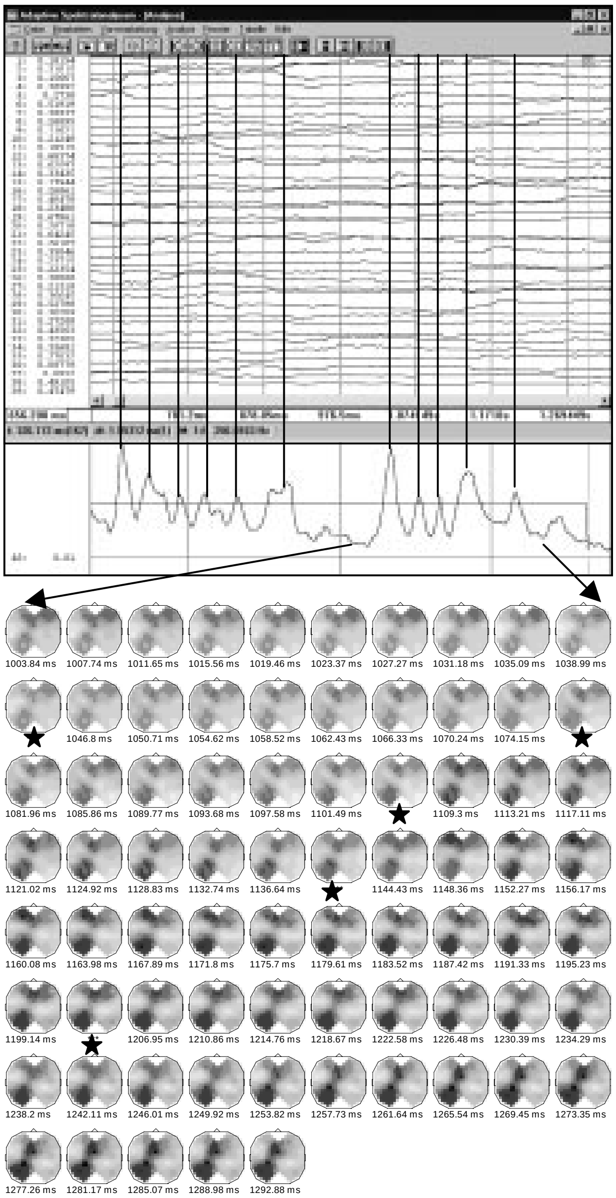


Fig.1: Demonstration of the segmentation procedure. Upper part: time course of the multidimensional coherence vector with segment boundaries. Middle part: time course of the segmentation function. Lower part: sequence of coherence maps with segment boundaries (asterisks) for the marked interval

vector coherences may be subdivided in time segments with similar vectors of coherence values. The similarity between two coherence vectors for two adjacent

short time intervals may be established by a weighted vector correlation. The weighted correlation between two vectors **a** = $(a_1,..,a_m)$ and **b** = $(b_1,..,b_m)$ is calculated by

$$w(\mathbf{a},\mathbf{b}) = \frac{\sum_{m=1}^{M} p_m a_m b_m}{\sqrt{\sum_{m=1}^{M} p_m a_m^2 \cdot \sum_{m=1}^{M} p_m b_m^2}} \quad , \qquad (2)$$

where **p** = $(p_1,..,p_M)$ denotes a weighting vector. In our case M = 30 is the number electrode pairs (dimension of the coherence vector). For each time point the mean coherence vectors $\mathbf{a}(t_k)$ and $\mathbf{b}(t_k)$ of two adjacent time windows were generated:

$$a_m(t_k) = \frac{1}{N} \sum_{j=k-N+1}^{k} (\rho^2)_{t_j}^m \quad \text{and} \quad b_m(t_k) = \frac{1}{N} \sum_{j=k+1}^{k+N} (\rho^2)_{t_j}^m \ , \qquad (3)$$

with m=1,...,30 and the moving window lengths N = 5. The inverse weighting vector

$$p_m(t_k) = \frac{1}{\left|a_m(t_k) \cdot b_m(t_k)\right|} \ , m = 1,..,30 \qquad (4)$$

was chosen. From equations (2)-(4) a segmentation function $w(t_k) = 1 - w(\mathbf{a}(t_k), \mathbf{b}(t_k))$ is build, which describes the local similarity of successive coherence vectors. Figure 1 shows an example of the time courses of the 30-dimensional coherence vector (upper panel) and the segmentation function $w(t_k)$ (middle panel). Afterwards, the 80%-quantile of the segmentation function was calculated for the whole time interval analyzed. Each maximum of the segmentation function which is greater than the 80%-quantile threshold served as a segment boundary (see Fig. 1). For each time segment the duration of the segment and the mean coherence vector were calculated. The lower panel in Fig. 1 shows the sequence of local coherence maps for the time interval marked by arrows. Asterisks mark segmentation boundaries. The segments founded in this way present stable microstates of synchronous oscillations.

Clustering of segments of coherence vectors

In order to obtain prototypical microstates a Fuzzy clustering for the mean values of the 30-dimensional coherence vectors of the segments was performed (see [5]). In order to predefine a suitable number of clusters the following investigations were performed. The mean values of coherence vectors of the segments were clustered with different number m of clusters, m = 2,...,10. The sum of squared Euclidian distances d_{jk}^2 between the vectors of the single segments and the corresponding cluster centers was calculated:

$$S(m) = \sum_{k=1}^{m} \sum_{j=1}^{n_m} d_{jk}^2 \quad , \qquad (5)$$

n_m is the number of segments corresponding to the k-th cluster center for the cluster number m. Then

$$R^2(m) = 1 - \frac{S(m)}{\sum_{n=1}^{N}(\mathbf{x}_n - \overline{\mathbf{x}})^2}, \tag{6}$$

presents the explanation of variance, where N denotes the global number of segments, $\mathbf{x}_n$ is the coherence vector of the n-th segment and $\overline{\mathbf{x}}$ is the mean coherence vector of all segments. Obviously, the explanation of variance increases monotonously with the increased number of clusters. A reduced rise of function (6) hints to a sufficient number of clusters. A more objective criterion is the following one:

$$K(m) = \sum_{k=1}^{m}\sum_{j=1}^{n_m} d_{jk}^2 + c \cdot m \ , \ 0 < c < 1, \ 2 \le m \le M \ . \tag{7}$$

The number of clusters is defined by the global minimum m_0 of the penalty term (7) with regard to m and the positive value c.

From clustering we get a sequence of segments with three parameters: duration of a segment, the 30-dimensional coherence vector of the associated cluster center and the number of the cluster center. The segment duration is a temporal attribute of these microstates, whereas the 30-dimensional coherence vector of the associated cluster center reflect the topographical distribution of oscillatory synchronization of the microstates.

Cluster sequences and Markovian chains

The third parameter of the clustered segments is the number of the correspondent cluster center and may be understood as a certain state of oscillatory activity. The probability of occurrence of each cluster center (or state) will be estimated by its relative frequency of occurrence. Shannon's entropy is quantified to measure the disorganization or randomness of occurrence of the states. Shannon's entropy is defined by

$$H = -\sum_{j=1}^{n_0} P(j) \cdot \mathrm{ld}(P(j)) \ , \tag{8}$$

where j, j = 1, ... , n_0, are the numbers of clusters and stand for the different states.

The sequence of microstates may be modeled by a Markovian chain. The transition probability $P(j/i)$ as an important feature of Markovian chains denotes the probability of occurrence of the cluster center j immediately after the occurrence of the cluster center i. The estimation results from the correspondent relative frequency of this event. The conditional entropy of occurrence of states under the assumption of i as the present state is defined as

$$H(i) = -\sum_{j=1}^{n_0} P(j/i) \cdot \mathrm{ld}(P(j/i)), \ i = 1, \dots, n_0, \tag{9}$$

where ld denotes the logarithm dualis. The conditional entropy measures how one state i predicts the subsequent states j. If the other states j are independent from the occurrence of the state i, it holds, that $P(j/i) = P(i)$ and the conditional entropy is equal to the primary entropy according to (8). In the opposite case the conditional entropy is less than the primary entropy. The difference

$$H_{red} = H - \sum_{i=1}^{n_0} P(i) \cdot H(i) \tag{10}$$

is called entropy reduction and reflects the sequential structure of the states. If the succession of the states is completely randomly, the entropy reduction is zero. The entropy reduction increases, if some of the states entail determined other states. In this case we allude to a strong sequential structure of the states.

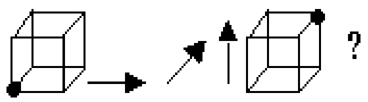
Experiment

In order to understand the special brain functioning of mathematically highly gifted subjects, we searched for a new measurement of the difference in the brain functioning of that group compared to normal subjects.

Twelve right handed mathematically highly gifted and twelve normal pupils carried out four different classes of tasks with different task complexity. The tasks were ordered by means of the number of modality strategies selectable in order to solve the problem: (i) mental navigation (one possible strategy), (ii) addition (one possible strategy [6]), (iii) elementary mathematical problems (two possible strategies) and (iv) complex mathematical problems (two possible strategies and activation).

Examples:

(i) Mental navigation: see below (imaginably solvable)



(ii) Addition: 5+3+9 = ? (computationally solvable).

(iii) Elementary problem: The length of the diagonal d of a square is 5 cm. How long is the length of an edge of a square with doubled area? (computationally ore imaginably solvable).

(iv) Complex problem: What is the number of diagonals of a 23-polygon? (computationally ore imaginably solvable).

The four kinds of tasks were given in blocks. Each task was presented on a computer screen. The navigation was evoked by the given strategy (arrows). Addition was performed by the known arithmetical algorithm. To solve an elementary or a complex problem the subjects have to select (and activate (iv)) one of the two possible strategies of computation or imagination.

The EEG was recorded from 19 scalp electrodes (10 /20 system, ear lob reference, 256 Hz).

The coherence analysis was focussed on the (13-20 Hz)-frequency band. This frequency band was found to be sensitive with regard to thinking processes (see Schack et al. 1999). The segmentation was performed as explained above. The cluster procedure was executed for each subject and each task separately.

III. RESULTS

Predefinition of the number of clusters: The number of clusters was predefined according to (5-7). Beginning with cluster number 6 the rise of the mean explanation of variance flattens. The investigation of the penalty criterion (7) objectifies this observation (compare Fig.2).

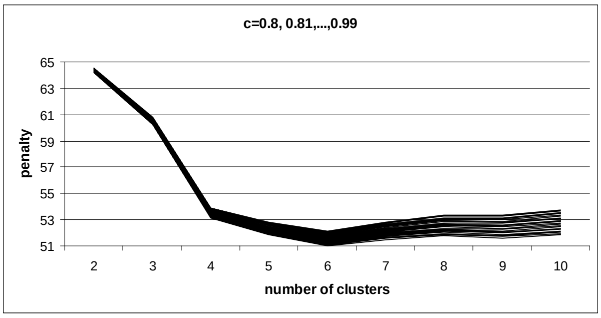


Fig. 2: Criterion (7) as a function of the number of clusters and the penalty term weighted by the variable c.

The global minimum of the penalty criterion was found for the cluster number 6. Further cluster analysis was performed with the fixed cluster number 6.

Entropy reduction: The entropy reduction was calculated according to (10) separately for each subject and each task.

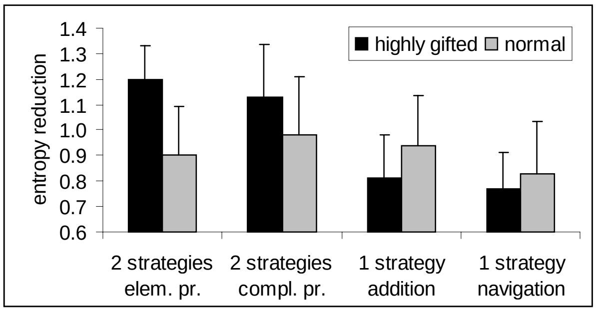


Fig.3: Mean values (and standard deviation) of entropy reduction for all subjects of the two groups

The difference of entropy reduction between mathematically highly gifted and normal subjects is a function of task complexity. There is a significant difference in the case of two modality strategies whereas no difference can be found with only one strategy (Fig.3).

Stability: The increase of entropy reduction is mainly caused by an increase in the self-transition probability of the microstates (highly gifted: 7% more than normal subjects Fig.4). The self-transition probability gives evidence about the strength of persistence in a state. A high self-transition probability hints to the stability in time of the correspondent microstate.

Again there is a significant difference in the case of two modality strategies whereas no difference can be found with only one strategy (Fig.4).

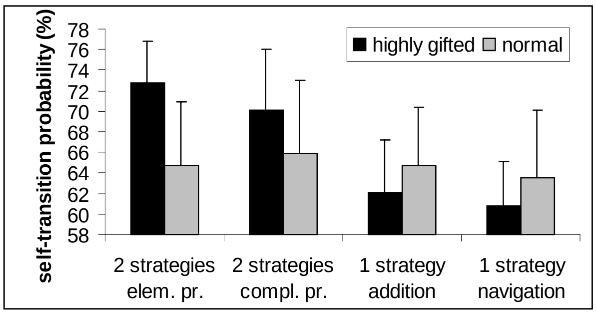


Fig.4: Mean values (and standard deviation) of self-transition probability in % for all subjects of the two groups

The self-transition probabilities are not equal for all six clusters. For both groups there are clusters with high and low stability. The self-transition probability is used to order the clusters within the two groups.

Topography: The coherence values (cluster centers) of ordered pairs may be compared. That means, prototypical states for mathematical gifted subjects and for normal subjects will be compared with respect to their order in stability. The coherence maps in Fig.5 shows the difference of coherence values for the 2 states with highest self-transition probability and for the 2 states with lowest self-transition probability for the task of solving a elementary mathematical problem. In the case of stable states coherences of the electrode pairs C3/P3, F7/F3 and C4/P4 are significantly higher for mathematically gifted subjects.

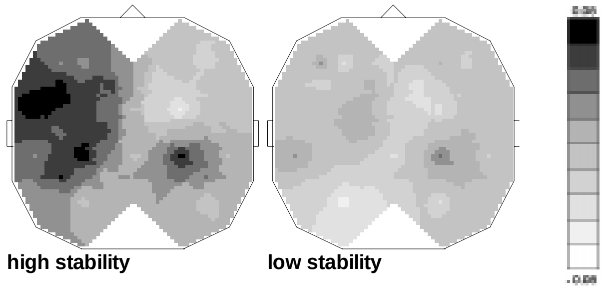


Fig.5: Maps of differences of coherence (mathematically gifted – normal).

IV. Discussion

The presented method of segmentation and clustering instantaneous EEG coherences enables the detection of stable prototypical microstates, and thus allows the analysis of higher mental processes e.g. thinking.

The identification of microstates is a precondition to consider a cognitive process as a Markovian chain. Against this background the strength of concatenation of microstates measurable as entropy reduction might be a new measure how cognitive processes may be organized. In summary this method is posing a fascinating challenge for future research to identify properties of thinking processes and to understand how this may interact with giftedness and ongoing experience.

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